CSE 5525: Foundations of Speech and Language Processing

Lecture 2: Binary Classification

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Many thanks to Prof. Greg Durrett @ UT Austin for sharing his slides.

Administrivia

- Course website updates
- HW#1 has been out, due 09/09/2020
- Final Project: Start forming teams (2-3 students with diverse background). Introduce yourself on Piazza and reach out to each other.

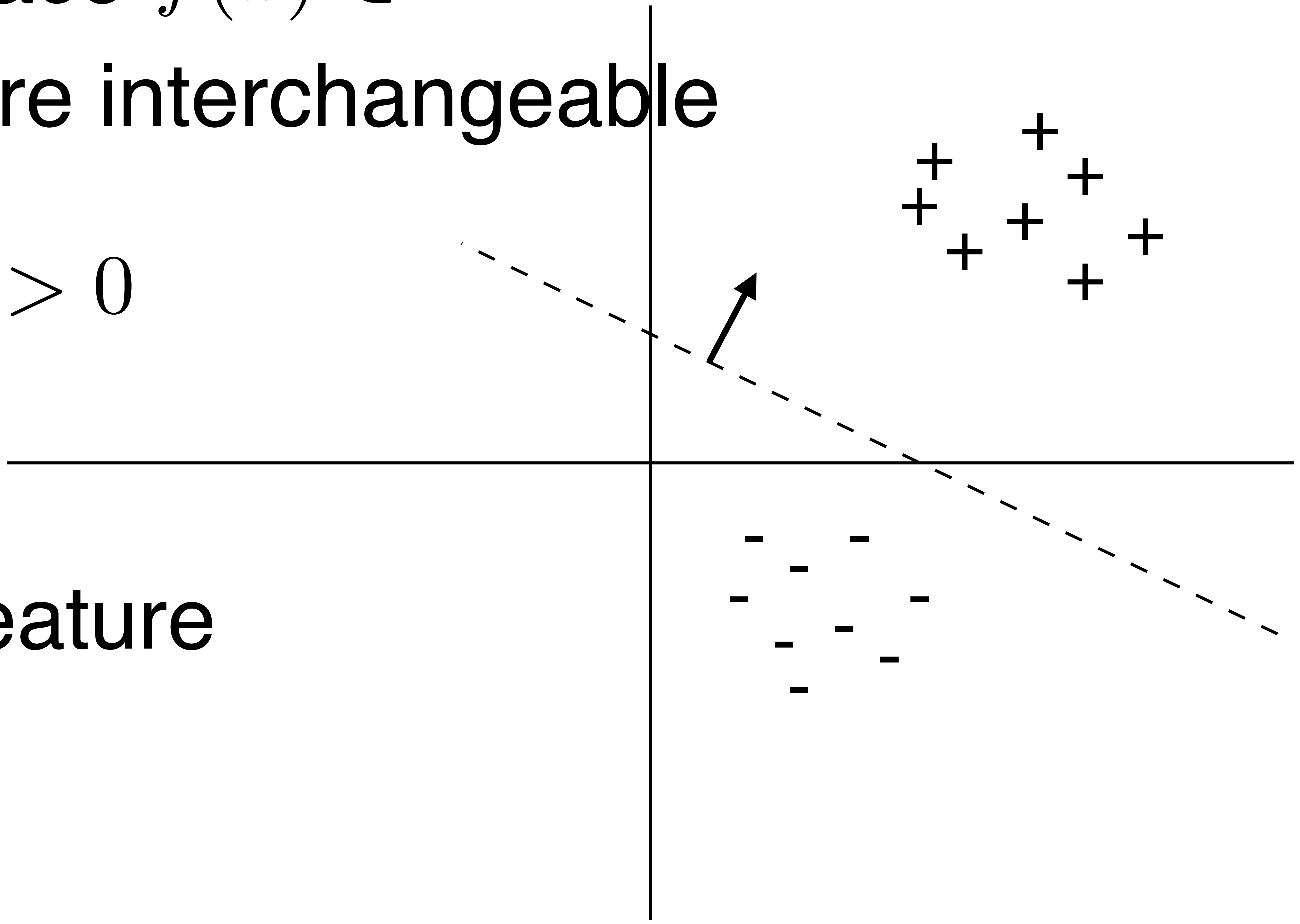
This Lecture

- Linear classification fundamentals
- Three discriminative models: logistic regression, perceptron, SVM
  - Different motivations but very similar update rules / inference!
- Optimization
- Sentiment analysis

Classification

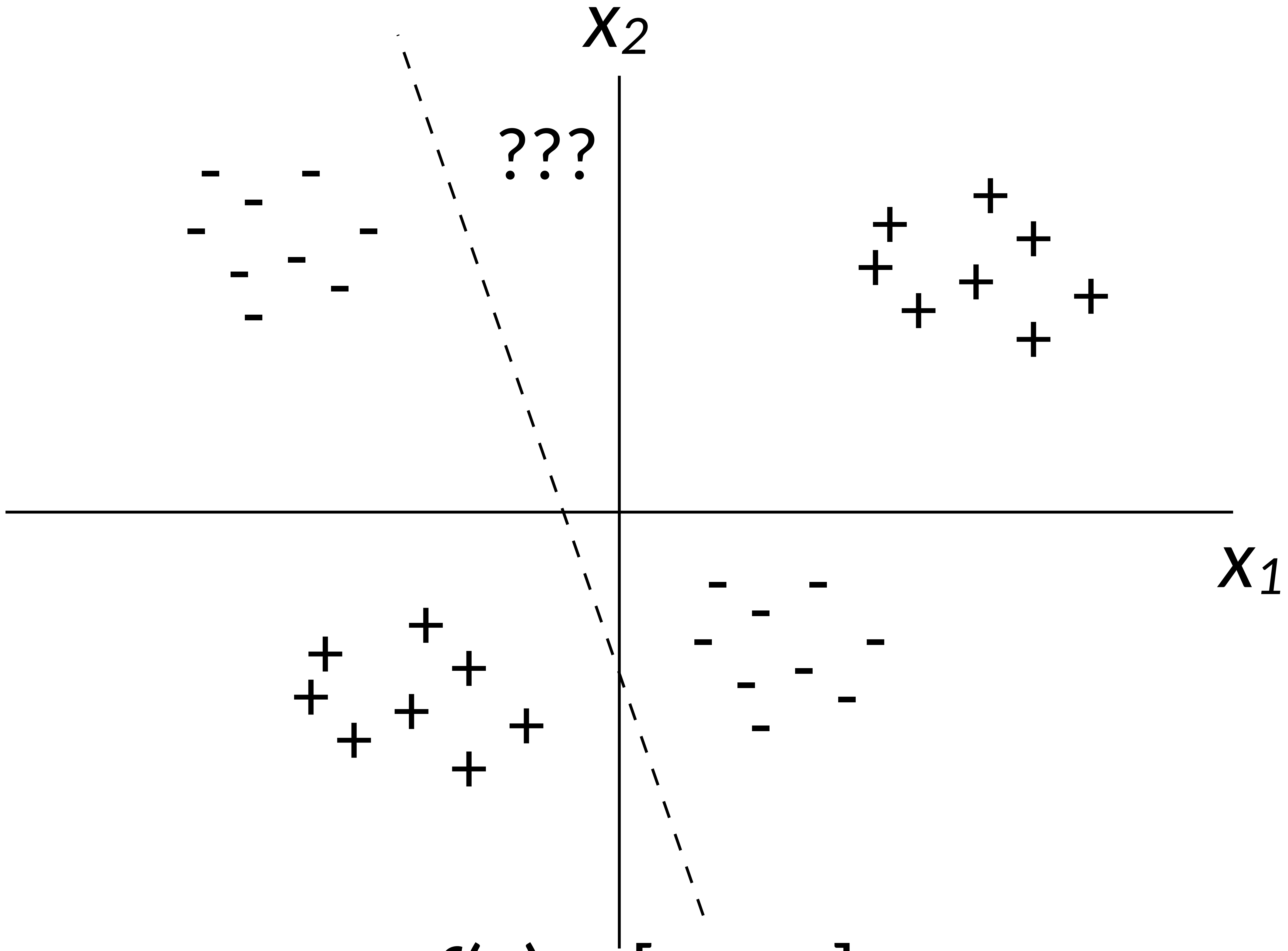
Classification

- Datapoint x with label $y \in \{0, 1\}$
- Embed datapoint in a feature space $f(x) \in \mathbb{R}^n$
  but in this lecture $f(x)$ and x are interchangeable
- Linear decision rule: $w^\top f(x) + b > 0$
  $w^\top f(x) > 0$

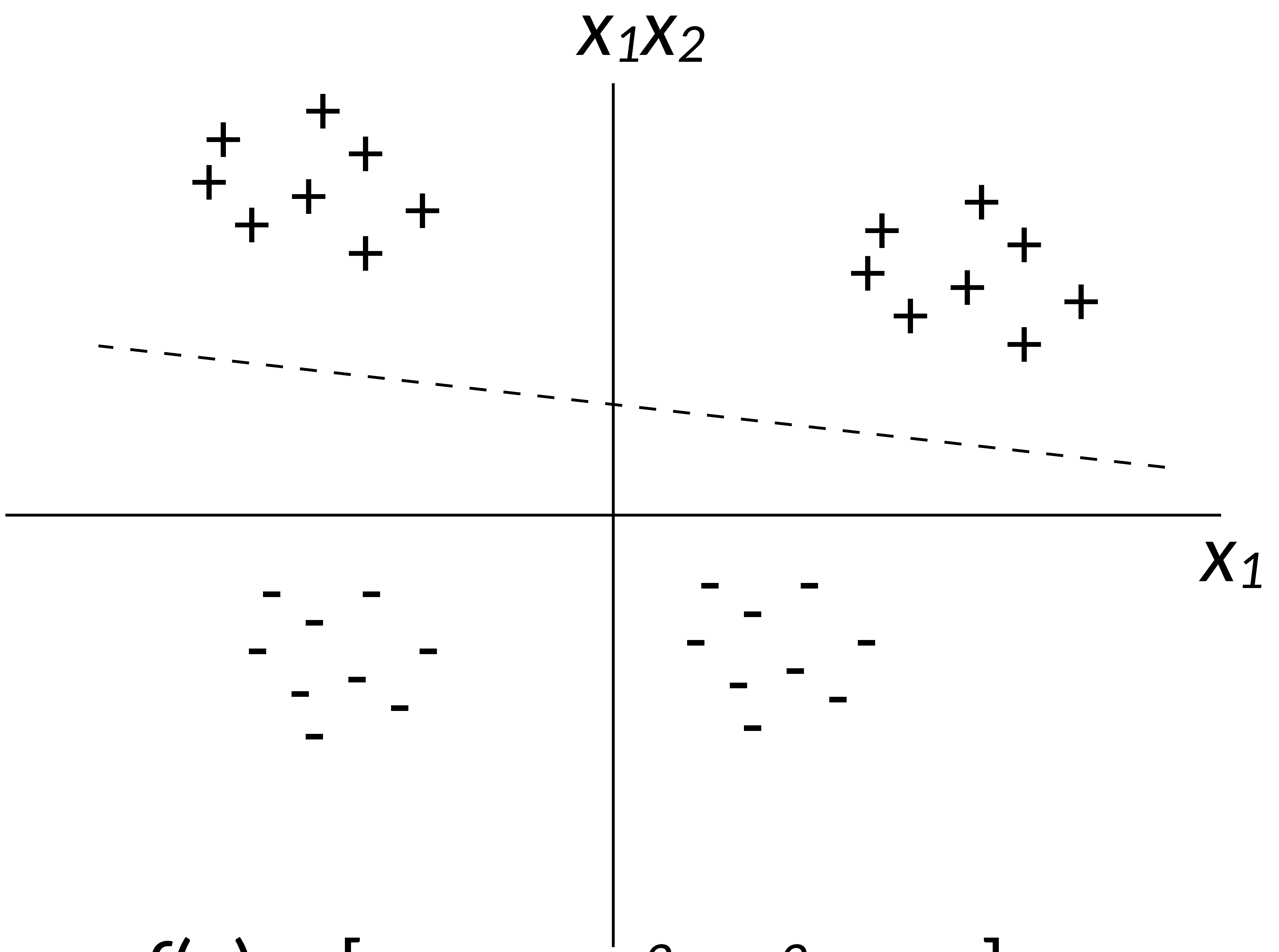


- Can delete bias if we augment feature space:
  $f(x)$ = [0.5, 1.6, 0.3]
  ↓
  [0.5, 1.6, 0.3, **1**]

Linear functions are powerful!



$f(x) = [x_1, x_2]$



$f(x) = [x_1, x_2, x_1^2, x_2^2, x_1x_2]$

- “Kernel trick” does this for “free,” but can be too expensive to use in NLP applications, training is $O(n^2)$ instead of $O(n \cdot (\text{num feats}))$

Classification: Sentiment Analysis

this movie was great! would watch again — Positive

that film was awful, I'll never watch again — Negative

- Surface cues can basically tell you what's going on here: presence or absence of certain words (*great*, *awful*)
- Steps to classification:
  - Turn examples like this into feature vectors
  - Pick a model / learning algorithm
  - Train weights on data to get our classifier

Feature Representation

this movie was great! would watch again Positive

- Convert this example to a vector using *bag-of-words features*

[contains *the*]	[contains *a*]	[contains *was*]	[contains *movie*]	[contains *film*]	...
position 0	position 1	position 2	position 3	position 4	
$f(x)$ = [0	0	1	1	0	...

- Very large vector space (size of vocabulary), sparse features (how many?)
- Requires *indexing* the features (mapping them to axes)
- More sophisticated feature mappings possible (tf-idf), as well as lots of other features: n-grams, character n-grams, parts of speech, lemmas, ...

Generative vs. Discriminative Modeling

- Data point $x = (x_1, ..., x_n)$, label $y \in \{0, 1\}$
- Generative models: probabilistic models of P(x,y)
  - Compute $P(y|x)$, predict $\text{argmax}_y P(y|x)$ to classify

$$P(y|x) = \frac{P(y)P(x|y)}{P(x)} \propto P(y)P(x|y)$$ "proportional to"

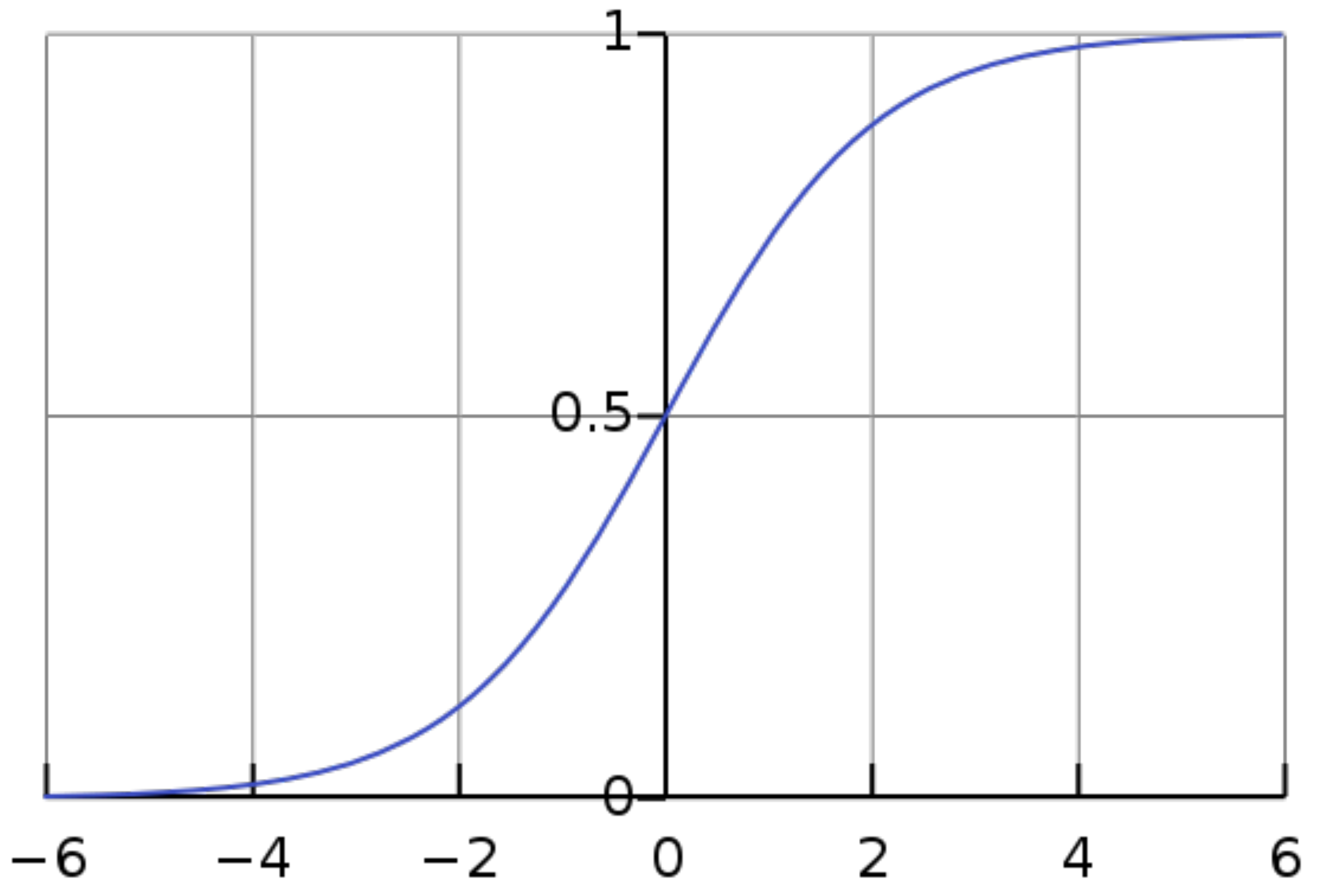
  - Examples: Naive Bayes (see textbook), Hidden Markov Models
- Discriminative models model P(y|x) directly, compute $\text{argmax}_y P(y|x)$
  - Examples: logistic regression
  - Cannot draw samples of x, but typically better classifiers

Logistic Regression

Logistic Regression

$$P(y = +|x) = \text{logistic}(w^\top x)$$

$$P(y = +|x) = \frac{\exp(\sum_{i=1}^{n} w_i x_i)}{1 + \exp(\sum_{i=1}^{n} w_i x_i)}$$



- To learn weights: maximize discriminative log likelihood of data (log P(y|x))

$$\mathcal{L}(\{x_j, y_j\}_{j=1,\ldots,n}) = \sum_j \log P(y_j|x_j)$$ corpus-level LL

$$\mathcal{L}(x_j, y_j = +) = \log P(y_j = +|x_j)$$ one (positive) example LL

$$= \sum_{i=1}^{n} w_i x_{ji} - \log\left(1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)\right)$$

sum over features

Logistic Regression

$$\mathcal{L}(x_j, y_j = +) = \log P(y_j = +|x_j) = \sum_{i=1}^{n} w_i x_{ji} - \log\left(1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)\right)$$

$$\frac{\partial \mathcal{L}(x_j, y_j)}{\partial w_i} = x_{ji} - \frac{\partial}{\partial w_i} \log\left(1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)\right)$$

$$= x_{ji} - \frac{1}{1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)} \frac{\partial}{\partial w_i}\left(1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)\right)$$

deriv of log

$$= x_{ji} - \frac{1}{1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)} x_{ji} \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)$$

deriv of exp

$$= x_{ji} - x_{ji} \frac{\exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)}{1 + \exp\left(\sum_{i=1}^{n} w_i x_{ji}\right)} = x_{ji}(1 - P(y_j = +|x_j))$$

Logistic Regression

- Gradient of w_i on positive example $= x_{ji}(1 - P(y_j = +|x_j))$

  If P(+) is close to 1, make very little update

  Otherwise make w_i look more like x_{ji}, which will increase P(+)

- Gradient of w_i on negative example $= x_{ji}(-P(y_j = +|x_j))$

  If P(+) is close to 0, make very little update

  Otherwise make w_i look less like x_{ji}, which will decrease P(+)

- Let $y_j = 1$ for positive instances, $y_j = 0$ for negative instances.
- Can combine these gradients as $x_j(y_j - P(y_j = 1|x_j))$

Example

(1) *this movie was great! would watch again* +

(2) *I expected a great movie and left happy* +

(3) *great potential but ended up being a flop* —

$f(x_1) = [1 \quad 1]$

$f(x_2) = [1 \quad 1]$

$f(x_3) = [1 \quad 0]$

[contains *great*] [contains *movie*]

position 0 position 1

$w = [0, 0]$ ⟶ $P(y = 1 \mid x_1)$ = exp(0)/(1 + exp(0)) = 0.5 ⟶ $g = [0.5, 0.5]$

$w = [0.5, 0.5]$ ⟶ $P(y = 1 \mid x_2)$ = logistic(1) ≈ 0.75 ⟶ $g = [0.25, 0.25]$

$w = [0.75, 0.75]$ ⟶ $P(y = 1 \mid x_3)$ = logistic(0.75) ≈ 0.67 ⟶ $g = [-0.67, 0]$

$w = [0.08, 0.75]$ …

$$P(y = +|x) = \text{logistic}(w^\top x)$$

$$x_j(y_j - P(y_j = 1|x_j))$$

Regularization

- Regularizing an objective can mean many things, including an L2-norm penalty to the weights:

$$\sum_{j=1}^{m} \mathcal{L}(x_j, y_j) - \lambda \|w\|_2^2$$

- Keeping weights small can prevent overfitting
- For most of the NLP models we build, explicit regularization isn't necessary
  - Early stopping
  - Large numbers of sparse features are hard to overfit in a really bad way
  - For neural networks: dropout and gradient clipping

Logistic Regression: Summary

- Model

$$P(y=+|x) = \frac{\exp(\sum_{i=1}^{n} w_i x_i)}{1+\exp(\sum_{i=1}^{n} w_i x_i)}$$

- Inference: for new x

$$\text{argmax}_y P(y|x)$$

$$P(y=1|x) \geq 0.5 \Leftrightarrow w^\top x \geq 0$$

- Learning: gradient ascent on the (regularized) discriminative log-likelihood

Perceptron/SVM

Perceptron

- Simple error-driven learning approach similar to logistic regression
- Decision rule: $w^\top x > 0$
  - If incorrect: if positive, $w \leftarrow w + x$

    if negative, $w \leftarrow w - x$

Logistic Regression

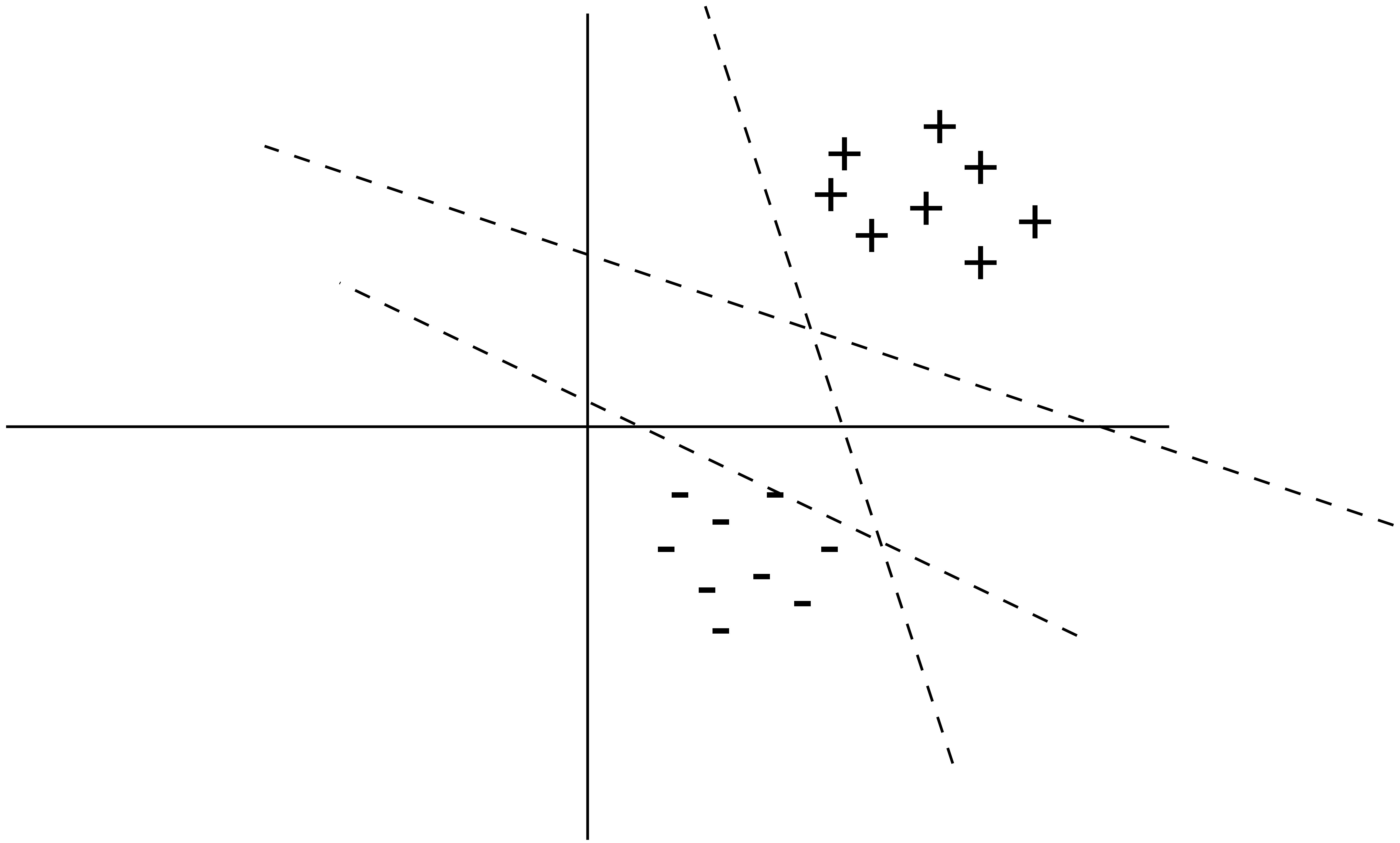
$$w \leftarrow w + x(1 - P(y = 1|x))$$

$$w \leftarrow w - xP(y = 1|x)$$

- Guaranteed to eventually separate the data if the data are separable

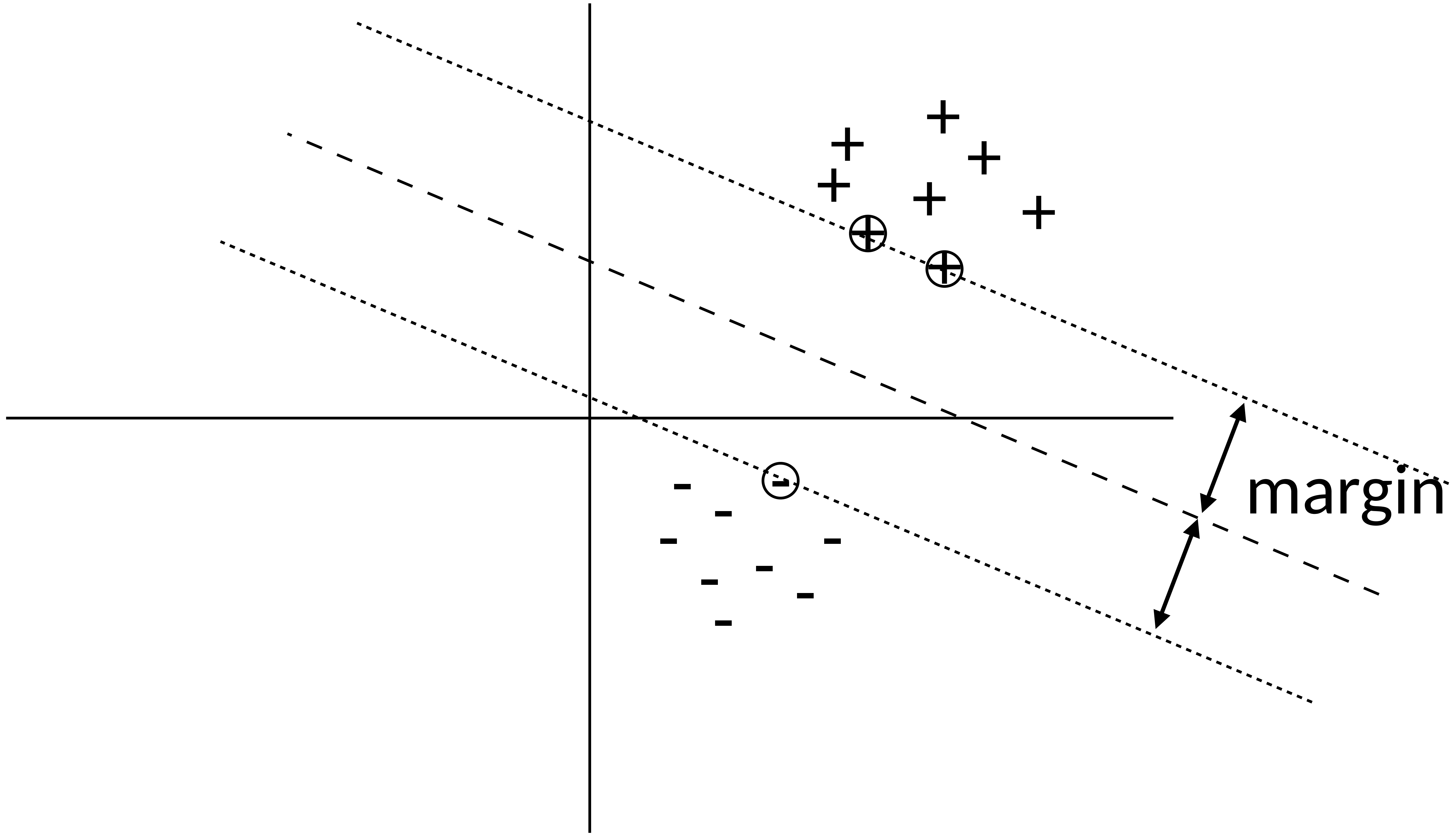
Support Vector Machines

- Many separating hyperplanes — is there a best one?



Support Vector Machines

- Many separating hyperplanes — is there a best one?



Support Vector Machines

- Constraint formulation: find *w* via following quadratic program:

Minimize $\|w\|_2^2$

s.t. $\forall j \quad w^\top x_j \geq 1 \text{ if } y_j = 1$

$$w^\top x_j \leq -1 \text{ if } y_j = 0$$

minimizing norm with fixed margin <=> maximizing margin

As a single constraint:

$$\forall j \quad (2y_j - 1)(w^\top x_j) \geq 1$$

- Generally no solution (data is generally non-separable) — need slack!

N-Slack SVMs

Minimize $\lambda \|w\|_2^2 + \sum_{j=1}^{m} \xi_j$

s.t. $\forall j \quad (2y_j - 1)(w^\top x_j) \geq 1 - \xi_j \qquad \forall j \quad \xi_j \geq 0$

- The ξ_j are a “fudge factor” to make all constraints satisfied
- Take the gradient of the objective:

$$\frac{\partial}{\partial w_i}\xi_j = 0 \text{ if } \xi_j = 0 \qquad \frac{\partial}{\partial w_i}\xi_j = (2y_j - 1)x_{ji} \text{ if } \xi_j > 0$$

$$= x_{ji} \text{ if } y_j = 1, \; -x_{ji} \text{ if } y_j = 0$$

- Looks like the perceptron! But updates more frequently

Gradients on Positive Examples

Logistic regression

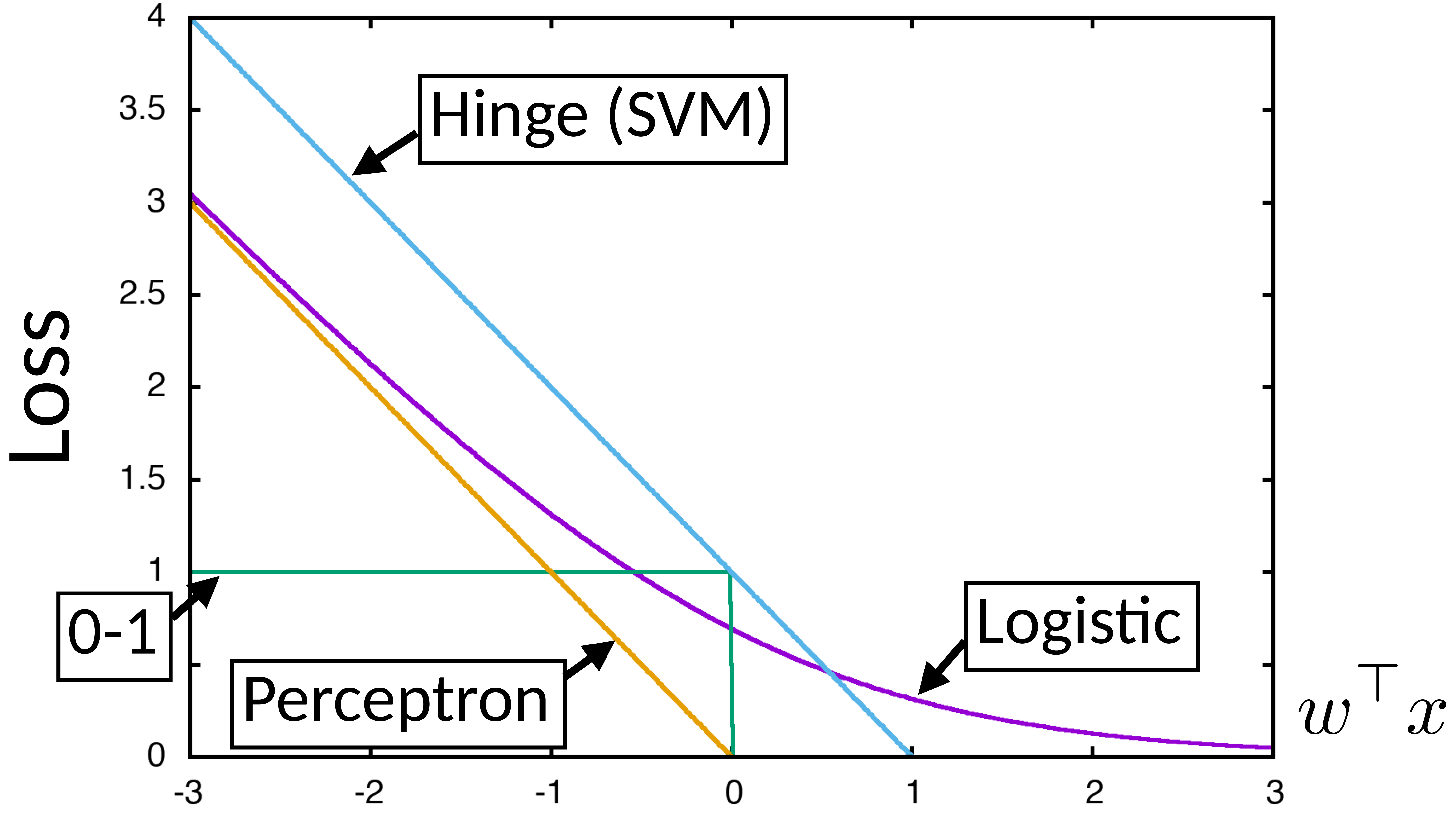
$$x(1 - \mathrm{logistic}(w^\top x))$$

Perceptron

$$x \text{ if } w^\top x < 0, \text{ else } 0$$

SVM (ignoring regularizer)

$$x \text{ if } w^\top x < 1, \text{ else } 0$$



*the left side shows the negative of the gradients of the loss functions, as we need to *minimize* the loss functions (i.e., w= w-g).

Comparing Gradient Updates (Reference)

Logistic regression (unregularized)

$$x(y - P(y = 1|x)) = x(y - \text{logistic}(w^\top x))$$

Perceptron

$(2y - 1)x$ if classified incorrectly

0 else

SVM

$(2y - 1)x$ if not classified correctly with margin of 1

0 else

y = 1 for pos,

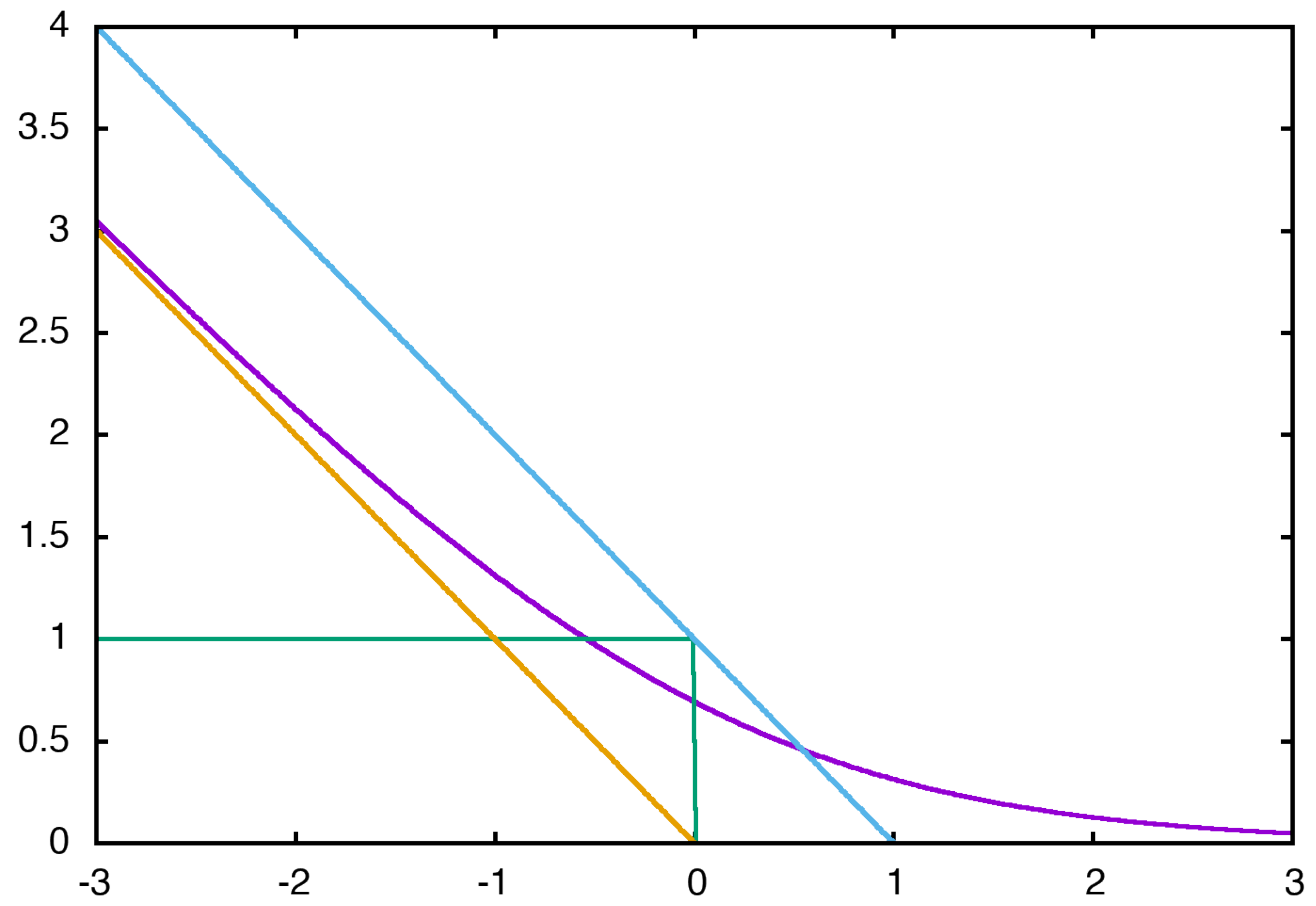
0 for neg

Read more connections here: https://www.cs.utexas.edu/~gdurrett/courses/sp2020/perc-lr-connections.pdf

Optimization

Structured Prediction

- Four elements of a structured machine learning method:
  - Model: probabilistic, max-margin, deep neural network
  - Objective



  - Inference: just maxes and simple expectations so far, but will get harder
  - Training: gradient descent?

Optimization

- Stochastic gradient *ascent*
  - Very simple to code up
  - "First-order" technique: only relies on having gradient
  - Can avg gradient over a few examples and apply update once (minibatch)
  - Setting step size is hard (decrease when held-out performance worsens?)

$$w \leftarrow w + \alpha g, \quad g = \frac{\partial}{\partial w}\mathcal{L}$$

- Newton's method
  - Second-order technique
  - Optimizes quadratic instantly

$$w \leftarrow w + \left(\frac{\partial^2}{\partial w^2}\mathcal{L}\right)^{-1} g$$

Inverse Hessian: *n* x *n* mat, expensive!

- Quasi-Newton methods: L-BFGS, etc. approximate inverse Hessian

AdaGrad

- Optimized for problems with sparse features

- Per-parameter learning rate: smaller updates are made to parameters that get updated frequently

$$w_i \leftarrow w_i + \alpha \frac{1}{\sqrt{\epsilon + \sum_{\tau=1}^{t} g_{\tau,i}^2}} g_{t_i}$$

← (smoothed) sum of squared gradients from all updates

- Generally more robust than SGD, requires less tuning of learning rate

- Other techniques for optimizing deep models — more later!

Duchi et al. (2011)

Sentiment Analysis

Sentiment Analysis

this movie was great! would watch again +

the movie was gross and overwrought, but I liked it +

this movie was not really very enjoyable —

- Bag-of-words doesn't seem sufficient (discourse structure, negation)
- There are some ways around this: extract bigram feature for "*not* X" for all X following the *not*

Bo Pang, Lillian Lee, Shivakumar Vaithyanathan (2002)

Sentiment Analysis

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	"	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

- Simple feature sets can do pretty well!

Bo Pang, Lillian Lee, Shivakumar Vaithyanathan (2002)

Sentiment Analysis

Method	RT-s	MPQA
MNB-uni	77.9	85.3
MNB-bi	**79.0**	**86.3**
SVM-uni	76.2	86.1
SVM-bi	77.7	**86.7**
NBSVM-uni	**78.1**	85.3
NBSVM-bi	**79.4**	**86.3**
RAE	76.8	85.7
RAE-pretrain	77.7	**86.4**
Voting-w/Rev.	63.1	81.7
Rule	62.9	81.8
BoF-noDic.	75.7	81.8
BoF-w/Rev.	76.4	84.1
Tree-CRF	77.3	86.1
BoWSVM	–	–
Kim (2014) CNNs	**81.5**	**89.5**

← Naive Bayes is doing well!

Ng and Jordan (2002) — NB can be better for small data

Before neural nets had taken off — results weren't that great

Wang and Manning (2012)

Sentiment Analysis

- Stanford Sentiment Treebank (SST) binary classification
- Best systems now: large pretrained networks
- 90 -> 97 over the last 2 years

Model	Accuracy	Paper / Source	Code
XLNet-Large (ensemble) (Yang et al., 2019)	96.8	XLNet: Generalized Autoregressive Pretraining for Language Understanding	Official
MT-DNN-ensemble (Liu et al., 2019)	96.5	Improving Multi-Task Deep Neural Networks via Knowledge Distillation for Natural Language Understanding	Official
Snorkel MeTaL(ensemble) (Ratner et al., 2018)	96.2	Training Complex Models with Multi-Task Weak Supervision	Official
MT-DNN (Liu et al., 2019)	95.6	Multi-Task Deep Neural Networks for Natural Language Understanding	Official
Bidirectional Encoder Representations from Transformers (Devlin et al., 2018)	94.9	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	Official
…			
Neural Semantic Encoder (Munkhdalai and Yu, 2017)	89.7	Neural Semantic Encoders	
BLSTM-2DCNN (Zhou et al., 2017)	89.5	Text Classification Improved by Integrating Bidirectional LSTM with Two-dimensional Max Pooling	

https://github.com/sebastianruder/NLP-progress/blob/master/english/sentiment_analysis.md

Recap

- Logistic regression: $P(y=1|x) = \frac{\exp\left(\sum_{i=1}^{n} w_i x_i\right)}{\left(1+\exp\left(\sum_{i=1}^{n} w_i x_i\right)\right)}$

  Decision rule: $P(y=1|x) \geq 0.5 \Leftrightarrow w^\top x \geq 0$

  Gradient (unregularized): $x(y - P(y=1|x))$

- SVM:

  Decision rule: $w^\top x \geq 0$

  (Sub)gradient (unregularized): 0 if correct with margin of 1, else $x(2y-1)$

Recap

- Logistic regression, SVM, and perceptron are closely related
- SVM and perceptron inference require taking maxes, logistic regression has a similar update but is "softer" due to its probabilistic nature
- All gradient updates: "make it look more like the right thing and less like the wrong thing"
- Next time: multiclass classification